Electroencephalogram data analysis using Convolutional Neural Networks and Gramian Angular Field

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Abstract. The paper proposes a binary classification model designed to analyze electroencephalograms data to detecting pathologies associated with epilepsy. The model is based on the Convolutional Neural Network. As input data for the neural network, images obtained by transforming the values of the original electroencephalograms time series based on the Gramian Angular Field matrix were used. The model was trained on data from the Temple University Hospital electroencephalograms Seizure Corpus open data source. The proposed model demonstrated high performance metrics: accuracy – 91%, precision – 92%, recall – 95%, F1-0.93.

1 Introduction

Modern healthcare systems are experiencing continuous growth in the volume of medical data processed and stored. This data is varied and may include tissue samples, clinical notes, genetic testing, medical images, etc. Processing big medical data using modern machine learning methods is widely used in various areas of healthcare and has significant potential for improving the quality of diagnosis and treatment of diseases [1].

One of the important tasks of modern medicine is the diagnosis and treatment of epilepsy [2]. Epilepsy is a common neurological disease characterized by involuntary seizure activity. This disease significantly worsens the quality of life of patients. Electroencephalography (EEG) is often used to diagnose epilepsy [3]. Traditional manual analysis of electroencephalographic recordings requires significant time and is subject to classification errors due to the subjectivity of the expert's assessment [4]. The development of automated methods for analyzing electroencephalograms will reduce the time and cost of EEG studies and improve the quality of diagnosis.

Advances of deep learning in computer vision have inspired researchers to develop methods that encode time series data into various types of images for further use as input data in classification tasks using convolutional neural networks (CNNs) [5]. The construction of Artificial Intelligence (AI) - based classifier, trained to recognize the presence of pathology

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in a certain time area of the electroencephalogram recording, will help a neurologist in making a final diagnosis, reducing the time for decoding recordings.

In this study, we transform the EEG signal into a set of images by converting the values of the original time series based on the Gramian Angular Field (GAF) matrix. The resulting images are then fed to a convolutional neural network to extract informative features from the input GAF images. The proposed model was trained and evaluated on a publicly available dataset of clinical electroencephalogram recordings from patients suffering from epilepsy.

2 Experimental design

2.1.1 Description of the dataset

To train and test the model, we used an open EEG dataset containing clinical records of patients with epileptic seizures of the Temple University Hospital (TUH) EEG Seizure Corpus (TUSZ) [6, 7]. This set was designed specifically for developing and testing supervised learning models and was hand-labeled by experts-neurologists. This set is large enough to train a neural network. The set contains both records containing pathological events and records that correspond to the norm. The experiment used a reduced sample of data from this dataset with class labels corresponding to the binary classification (normal/pathological).

2.1.2 Data preparation

A set of .edf files of the original dataset was loaded into a Postgres database to facilitate data manipulation. The EEG data were converted from a monopolar montages scheme to a bipolar scheme. To optimize the hyperparameters of the model, fit the model and evaluate the final performance of the model, the source data was divided into a training, validation and test set in a proportion of 65%, 20% and 15% respectively.

2.1.3 Feature extraction

The selection of salient informative features for training machine learning model in data mining tasks is no less important than building the model. Electroencephalogram recordings belong to complex types of data called Sequence Data. Examples of sequential data include data such as the sequence of customer purchases stock market data, symbolic sequences (e.g., web click streams), biological sequences (e.g., DNA and protein sequences) [8].

Electroencephalograms are long-term time series of time-ordered observations made at equal time intervals (equidistant time series). The sampling rate for the data set we used is 250 Hz. For such data, data dimensionality is often reduced based on some transformation, when the original data is transformed (projected) into some new space of informative features. Thus, feature extraction is a type of data dimensionality reduction in which fewer values are calculated based on some large number of values. These values still contain the information necessary for the model to work, and, at the same time, allows to get rid of redundant information [1].

We chose a technique for extracting informative features based on converting the original time series into a set of images using the Gramian Angular Field (GAF) matrix [5]. To do this, the original time series was divided into non-overlapping windows 224 samples wide (~1 s).

The Gramian Summation Angular Field (GASF) matrix conversion method includes the following steps [9]:

1. Rescale of the original time series **X**=($x_1, x_2, \ldots, x_n$) into the interval [-1,1] in accordance with formula (1):

$$\widehat{x_i} = \frac{(x_i - \max(\boldsymbol{X})) + (x_i - \min(\boldsymbol{X}))}{\max(\boldsymbol{X}) - \min(\boldsymbol{X})}. \quad (1)$$

2. Transformation of a normalized series into a polar coordinate system in which amplitude values in the form of an angular cosine and time values in the form of a radius are encoded in accordance with the formula (2):

$$\begin{cases} \varphi_i = \arccos(\widehat{x_i}), \\ r_i = \frac{t_i}{N}, \end{cases} \quad (2)$$

where t_i is the time value at point i, N is the full time interval.

3. Construction of matrix G in accordance with the formula (3):

$$G = \begin{bmatrix} \cos(\varphi_1 + \varphi_1) & \cdots & \cos(\varphi_1 + \varphi_n) \\ \cos(\varphi_2 + \varphi_1) & \cdots & \cos(\varphi_2 + \varphi_n) \\ \vdots & \ddots & \vdots \\ \cos(\varphi_n + \varphi_1) & \cdots & \cos(\varphi_n + \varphi_n) \end{bmatrix}. \quad (3)$$

4. Formation of an image based on the resulting matrix G.

Figure 1 shows an example of converting a fragment of an EEG time series into an image based on the Gram matrix.

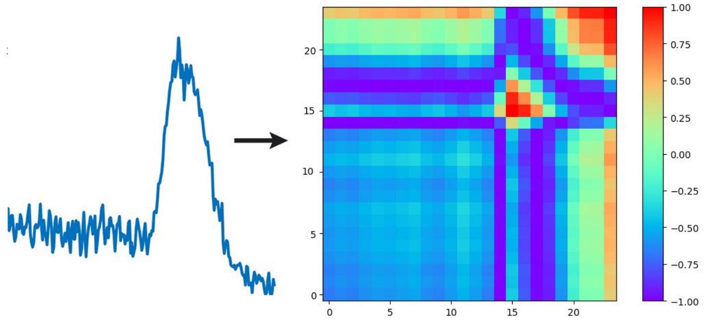

Fig. 1. An example of converting an EEG signal into an image based on the Gramian Summation Angular Field (GASF).

2.1.4 Model selection

Selecting an appropriate machine learning model for solving real biomedical problems is a complex task and depends on many factors, such as the nature of the source data, its volume, the quality of data preprocessing, the presence of noise, requirements to the result accuracy, algorithm speed, and many others.

The specificity of the problem of identifying epileptic events in electroencephalogram recordings is the low signal-to-noise ratio (SNR), the high degree of individual differences in the EEG for different patients, as well as the imbalance of the data set resulting from the nature of the task. Epileptic events are rare compared to normal, accounting for less than one percent of the total in the data set we used. Imbalanced data requires the use of special techniques, since not all algorithms work well enough with such data sets.

In our work, the task of identifying epileptic events was considered as a supervised learning task, namely, as a binary classification problem. The pathology was chosen as the positive (target) class, and the norm was chosen as the zero class. A model based on a convolutional neural network (CNN) was chosen as a model for binary classification.

A two-dimensional image was fed to the input of the model; the result of a binary classification (1-pathology, 0-norm) is expected at the output. Quality metrics were assessed using a delayed test sample of images. Cross-entropy is adopted as the training loss function. ADAM was chosen as the optimizer.

2.1.5 Model realization

For the experiments, the AlexNet neural network architecture was used [10]. A schematic representation of the AlexNet network architecture is presented in Figure 2.

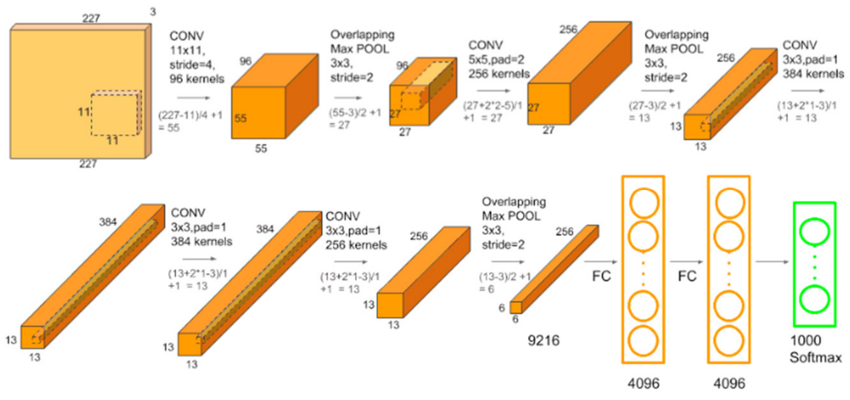

Fig. 2. The example of AlexNet Network Architecture realization [11]

The software implementation of the network model was performed in Python using the Pytorch framework [12].

2.1.6 Performance testing

The classification results were evaluated using the following model performance metrics [4]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{6}$$

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{7}$$

Where TP is True Positives, FP is False Positives, FN is False Negatives, TN is True Negatives. Table 1 presents the performance metrics of the proposed model on the test data set.

Table 1. Performance Metric Values

	AlexNet
Accuracy	0.91
Macro-Avg Precision	0.92
Macro-Avg Recall	0.95
Macro-Avg F1	0.93

3 Conclusion

In this work, we tested the architecture of the AlexNet neural network in relation to the task of detecting epileptic seizures using electroencephalogram data. The tested neural network model belongs to the type of convolutional neural networks. The Temple University Hospital (TUH) EEG Seizure Corpus (TUSZ) open dataset of clinical electroencephalograms records was used as a data source. The input data for the neural network was images generated using a Gram matrix-based transformation from a time series of electroencephalogram recordings. A similar approach was used in [13] on the Physionet EEG MI test set for classifying motor images. The CNN-LSTM model used in it showed 84.18% accuracy. The model used in this work showed better performance results. Testing on a deferred test sample showed high values of model performance metrics: accuracy – 0.91, recall – 0.95, precision – 0.92 and F1 – 0.93. The obtained results shows that the method based on the use of CNN in combination with the GAF transformation for representation of informative features of EEG recordings is effective in tasks of binary classification for identifying epileptic seizures. Further research to improve the network architecture and optimize its hyperparameters will contribute to the development of EEG classification methods suitable for use in clinical practice.

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